

Prediction of scour below submerged pipeline crossing a river using ANN

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ABSTRACT

The process involved in the local scour below pipelines is so complex that it makes it difficult to establish a general empirical model to provide accurate estimation for scour. This paper describes the use of artificial neural networks (ANN) to estimate the pipeline scour depth. The data sets of laboratory measurements were collected from published works and used to train the network or evolve the program. The developed networks were validated by using the observations that were not involved in training. The performance of ANN was found to be more effective when compared with the results of regression equations in predicting the scour depth around pipelines.

Key words | artificial neural networks, local scour, pipelines, regression

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NOTATION

d_{50}	particle mean diameter
d_s	equilibrium scour depth
D	the diameter of the pipe
F_r	Froude number
g	gravitational acceleration
Q	discharge
R_e	Reynolds number
S_f	slope of the energy line
V	flow velocity
Y	flow depth
ν	fluid kinematic viscosity
ρ	fluid density
ρ'_s	buoyant sediment density
τ_*	dimensionless Shields parameter

INTRODUCTION

The underwater pipeline structures are usually exposed to currents, waves, and combined waves and currents. This situation usually causes an increase in the local sediment transport capacity and thus leads to scour, which is a threat to the stability of the structure. Scour underneath the pipeline may expose a section of the pipe, causing it to become unsupported (Figure 1). In the case of pipe lines with a long free span, scour causes resonant flow-induced

oscillations of the pipes, leading to structural failure. The scour phenomenon involves the complexities of both the three-dimensional flow pattern and sediment movement. Accurate estimate of the scour depth is important in the design of submarine pipelines (Chiew 1991).

Substantial research was carried out, and is still underway, on the estimation of the scour characteristics of underwater pipelines. A number of empirical correlations were developed in the past to estimate equilibrium scour depth below pipelines, by Dutch Research Group (Bijker & Leeuwestein 1984), Moncada & Aguirre (1999), and Chiew (1991). However, these empirical equations, as summarized in Table 1, did not give the actual scour depth.

Recently the strengths of artificial neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) in estimating the scour around and downstream of hydraulic structures have been demonstrated by Azamathulla *et al.* (2008). In a similar study, they (Azamathulla & Ghani 2010) proved that ANN is effective to achieve reasonably good solutions for hydraulic-engineering problems, particularly for cases of highly nonlinear and complex relationships among the input-output pairs. This study presents ANN as an alternative tool in the prediction of scour below pipeline. The feed forward back propagation (FFBP) technique is employed to develop a predictive model for scour depth. The performance of the proposed FFBP model is compared with a conventional regression-based equation.

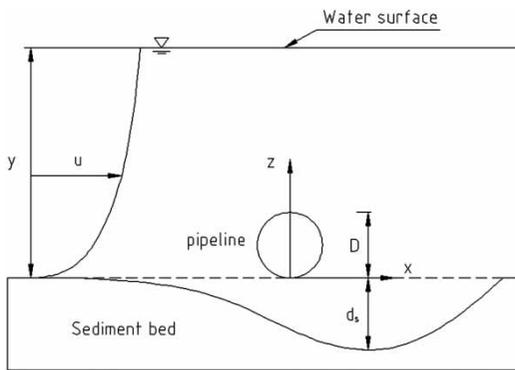


Figure 1 | Local scour below pipeline in river crossing.

Table 1 | Empirical formulae for estimation of pipeline scour depth

Author	Equation
Ibrahim & Nalluri (1986)	$\frac{d_s}{D} = 4.706 \left(\frac{U_0}{Uc} \right)^{0.89} \left(\frac{U_0}{gy} \right)^{1.48} + 0.06 \text{ clearwater}$ $\frac{d_s}{D} = 0.084 \left(\frac{U_0}{Uc} \right)^{-0.8} \left(\frac{U_0}{\sqrt{gy}} \right)^{-0.16} + 1.33 \text{ livebed}$
Dutch Research Group (Bijker & Leeuwestein 1984)	$d_s = 0.929 \left(\frac{U_0}{2g} \right)^{0.26} D^{0.79} d_{50}^{-0.04}$
Moncada & Aguirre (1999)	$\frac{d_s}{D} = 0.9 \tanh(1 + 1.4F) + 0.55, \quad \frac{d_s}{D} = 2F \sec\left(1.7 \frac{e}{D}\right)$ <p>D = pipe diameter, e = initial gap between pipe and undisturbed erodible bed</p>

ANALYSIS OF LOCAL SCOUR BELOW UNDERWATER PIPELINES

The variables influencing the equilibrium scour depth (d_s) below a pipeline in a steady flow over a bed of uniform, spherical and cohesionless sediment are: flow condition, sediment characteristics, and pipe geometry. The scour depth can be represented by the following general functional relationship (Moncada & Aguirre 1999):

$$d_s = f(\rho, \rho'_s, \nu, Q, Y, g, d_{50}, S_f, D) \quad (1)$$

where ρ = fluid density, ρ'_s = buoyant sediment density, ν = fluid kinematic viscosity, Q = discharge, Y = flow depth, g = gravitational acceleration, d_{50} = particle mean diameter,

S_f = slope of the energy line, D = the diameter of the pipe, and d_s = equilibrium scour depth.

The nine independent variables in Equation (1) can be reduced to a set of six non-dimensional parameters. The Buckingham pi (or π) theorem applied to Equation (1), choosing ρ , Q and D as basic variables, leads to:

$$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, Re, S_f, F\right) \quad (2)$$

where $\tau_* = \gamma S_0 / \Delta d_{50}$ dimensionless Shields parameter related to sediment transport, $\Delta = (\rho_s - \rho) / \rho$, D/d_{50} = dimensionless soil characteristics, $Re = VD/\nu$ = Reynolds number, S_f = slope of the energy line, and $F = V/\sqrt{gY}$, Froude number. The influence of Reynolds number is considered negligible under a fully turbulent flow over a rough bed (Lim & Chiew 2001; Melville 1992). The experimental data consisting of 215 data sets were collected from the works of Moncada & Aguirre (1999), and Dey & Singh (2008).

STATISTICAL REGRESSION MODEL

The dimensionless groups of parameters in Equation (2) were related to each other in the present study on the basis of nonlinear regression using 75% of the measurements selected randomly. This yielded the following equations in order to estimate the maximum scour depth:

$$\frac{d_s}{D} = 2.5\tau_*^{0.05} \left(\frac{Y}{D}\right)^{0.4} \left(\frac{D}{d_{50}}\right)^{0.35} (Re)^{0.25} (F)^{0.47} \quad (3)$$

Validation of Equation (3) was made with the help of the remaining 25% of observations, which were not involved in their derivation.

DEVELOPMENT OF NEURAL NETWORK MODEL

ANN provides a random mapping between an input and an output vector, typically consisting of three layers of neuron, namely, input, hidden and output, with each neuron acting as an independent computational element. Neural networks derive their strengths from the high degree of freedom associated with their architecture. Prior to application, the network is trained to the observed data sets. This feeds the network with input and output pairs and determines the values of connection weights, and bias. The training may require many epochs

(presentation of complete data sets once to the network), being carried out until the training sum of squares error reaches a specified error goal. Concepts involved behind these training schemes are outlined in the [ASCE Task Committee \(2000\)](#). A neural network toolbox contained within the MATLAB package was used in this study. The usual feed-forward type of network was trained using FFBP. Out of the total of 215 input-output pairs, about 75% (161 sets), selected randomly, were used for training, whereas the remaining 25% (54 sets) were employed for testing. As dictated by the use of a sigmoid function, all patterns were normalized within the range of 0.0, 1.0 before their use.

The FFBP models were developed; the first combination (FFBP model 1 as shown in [Figure 2](#)) involves just four (Q , Y , d_{50} , D) of the nine parameters in Equation (1) as the input pattern and the equilibrium scour depth (d_s) as

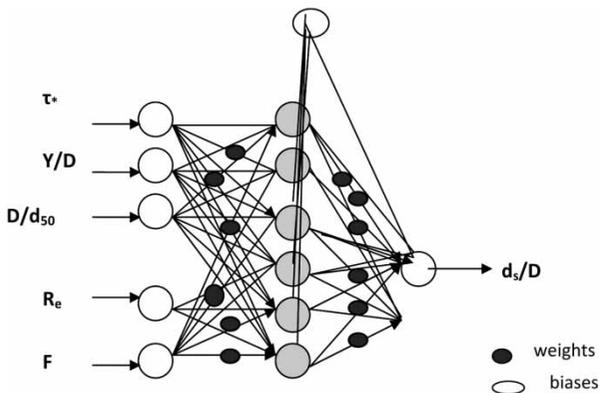


Figure 2 | Neural network architecture for FFBP model 1 (four inputs, six hidden neurons and one output).

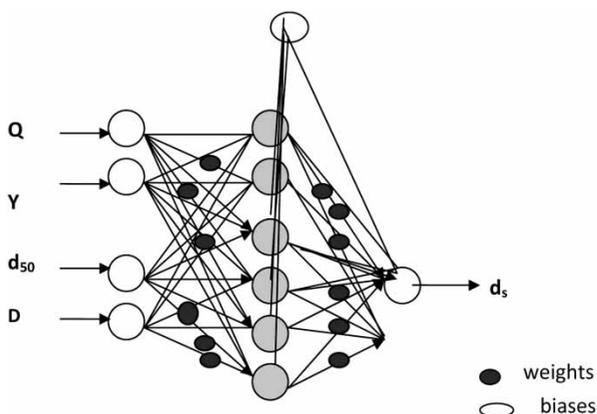


Figure 3 | Neural network architecture for FFBP model 2 (five inputs, 36 hidden neurons and one output).

the output pattern. Five of nine parameters in Equation (1), namely fluid density, the buoyant sediment density, fluid dynamic viscosity, gravitational acceleration and the slope of energy line, are constant in all experiments. The second combination includes the six non-dimensional parameters of Equation (2), and normalized equilibrium scour depth (d_s/D), as the input and output patterns, respectively.

Therefore, the second combination (FFBP model 2 as shown in [Figure 3](#)) (five inputs, 36 hidden neurons and one output) was trained.

TRAINING AND TESTING RESULTS OF FFBP MODEL

The performance of FFBP in training and testing sets is validated in terms of the common statistical measures R^2 (coefficient of determination), $RMSE$ (root mean square error), MAE (mean average error), and δ (average absolute deviation).

[Table 2](#) shows the range of variation of collected data for this study and its parameters.

The performances of all models were compared using the following four error measures:

$$R^2 = 1 - \frac{\sum_{i=1}^N (o_i - t_i)^2}{\sum_{i=1}^N (o_i - \bar{o}_i)^2} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (o_i - t_i)^2}{N}} \quad (5)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |o_i - t_i| \quad (6)$$

$$\delta = \frac{\sum |o_i - t_i|}{\sum o_i} * 100 \quad (7)$$

where t_i denotes the target values of equilibrium scour depth (cm), while o_i and \bar{o}_i denote the observed and averaged observed values of equilibrium scour depth (cm), respectively, and N is the number of data points. First, an attempt was made to assess the significance or influence of each input parameter on estimated d_s/D values. [Table 3](#) compares the FFBP models, with one of the independent parameters removed in each case, and deleting any independent parameter from the input set yielded larger $RMSE$ and lower R^2 values. These six independent parameters have non-negligible influence on d_s/D and so

Table 2 | Pipeline data and characteristics

Parameters	Unit	Data Range	Mean	Std Dev
<i>(a) Range of different input–output parameters used for the estimation of scour depth</i>				
Flow discharge (Q)	cm ³ /s	7–94.42	35.11	21.74
Flow depth (Y)	cm	3.8–28	13.43	6.21
Particle mean diameter (d_{50})	cm	0.234–0.7	0.437	0.144
Diameter of the pipe (D)	cm	0.48–7.6	1.92	1.61
Equilibrium scour depth (d_s)	cm	0.02–11.3	4.75	2.39
<i>(b) Range of different non-dimensional input–output parameters used for the estimation of scour depth</i>				
Dimensionless Shields parameter (τ_*)		0.038–0.70	0.23	0.17
Normalized flow depth (Y/D)		1.06–7	3.14	1.2
Pipeline diameter cross section of sediment size (D/d_{50})		3.28–145.8	38.17	31.41
Froude number (F_r)		0.2–0.83	0.46	0.15
Reynolds number R_e is normally used		700–9,450	3,250	2,174
Non-dimensional equilibrium scour depth (–)		0.008–1.66	1.04	0.32

Table 3 | Sensitivity analysis for independent parameters for the testing set

Model	RMSE	MAE	R ²
$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, R_p, F\right)$	0.05	0.33	0.93
$\frac{d_s}{D} = \Psi\left(\frac{Y}{D}, \frac{D}{d_{50}}, R_p, F\right)$	0.06	0.43	0.81
$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{D}{d_{50}}, R_p, F\right)$	0.07	0.53	0.82
$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{Y}{D}, R_p, F\right)$	0.09	0.74	0.72
$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, F\right)$	0.14	0.85	0.83
$\frac{d_s}{D} = \Psi\left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, R_p\right)$	0.24	0.97	0.64

the functional relationship given in Equation (2) is used for the FFBP modelling in this study. The FFBP (model 2) approach resulted in a highly nonlinear relationship between d_s/D and the input parameters with high accuracy and relatively low error. The testing performance of the proposed FFBP model revealed a high generalization capacity with $R^2 = 0.93$, $RMSE = 0.05$, $MAE = 0.33\%$ (Table 3).

RESULTS AND DISCUSSION

A regression equation (Equation (3)) was developed for preliminary scour depth estimation; but this equation failed to predict scour depth accurately, as it produced only $R^2 = 0.55$ for validation (testing set). Then the FFBP neural network was trained with different combinations (FFBP model 1 and FFBP model 2). The dimensional parameter combinations were flow discharge (Q), the flow depth (Y), particle mean diameter (d_{50}), diameter of the pipe (D) and the equilibrium scour depth (d_s). The non-dimensional parameters included Shields parameter related to sediment transport, pipeline diameter, cross section of grain size (d_{50}) and the Froude number. FFBP model 2 was developed and tested for predicting pipeline scour depth and also each parameter used in Equations (1) and (2) was considered in turn in the FFBP for sensitivity analysis (Table 3). It was shown by the sensitivity analysis that Shields parameter (τ_*) and Y/D have the highest and the least effect, respectively, on normalized scour depth with $RMSE = 0.06$, $MAE = 0.43$ and $R^2 = 0.81$. To assess the performance of the FFBP model 2, the observed equilibrium scour depth values were plotted against the predicted ones. Figures 4(a) and 4(b) illustrate the results with the performance indices between predicted and observed data for the training and validating (testing) data sets, for dimensional and non-dimensional parameters respectively, for both the models. As can be seen from Table 4, the first combination (original data) has a better ability to predict the scour depth ($R^2 = 0.82$),

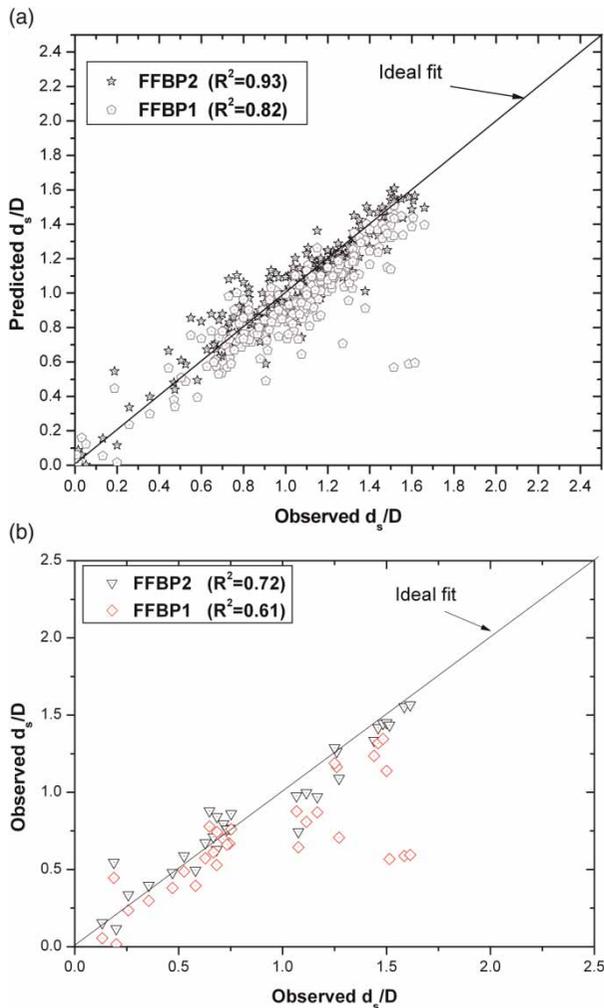


Figure 4 | Scatter plot of observed and predicted scour depth using FFBP model 1 and 2: (a) training and (b) validation (testing).

compared to the second combination ($R^2 = 0.93$). However $RMSE$ ($=0.04$) in second combination is better than first combination ($RMSE = 0.09$) in both training and testing, but this variation is low compared with the R^2 variation. FFBP model 1 failed to predict when data set $d_s/D < 0.4$, and also between $d_s/D < 0.4$ and $d_s/D < 1.8$; from Figure 4(a) it is clear that FFBP model 1 has underestimated d_s/D .

Table 4 | Comparison of models for dimensional set performance of the FFBP models (1 and 2)

Error measures	Training		Validation	
	FFBP model 2	FFBP model 1	FFBP model 2	FFBP model 1
R^2	0.93	0.82	0.72	0.61
$RMSE$	0.04	0.09	0.09	0.09
MAE	1.28	1.94	1.43	2.82
δ	5.65	11.53	10.35	15.83

Almost perfect agreement with the observed values was achieved with FFBP model 2. In general, the performance of FFBP model 2 was superior to the other methods, while the performance of Equation (3) was comparable to that of FFBP model 1. For practical problems, using an easy method, which is usable for different cases, is more acceptable than traditional methods. Also, using the low cost public domain software would be satisfactorily effective for researchers and engineers, especially students, instead of costly software such as MATLAB, GPLAB and Neuro Solutions.

CONCLUSION

A FFBP model was developed to predict the values of relative scour depth from the laboratory measurements. A new approach was presented to estimate equilibrium depth scour below underwater pipelines in river crossing from optimum data sets with the ANNs modelling technique. The application of the FFBP model 2 in this study is another important contribution to scour-depth estimation methodologies for pipes. The present study indicates that employing the original data set yielded a network that could predict measured pipeline depth scour in rivers more accurately than standard regression analysis. The overall performance of FFBP model 2 is superior to FFBP model 1.

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